IET Cyber-Physical Systems: Theory & Applications

Research Article

Cyber–physical microgrid components fault prognosis using electromagnetic sensors

ISSN 2398-3396
Received on 6th November 2017
Revised 21st October 2018
Accepted on 11th December 2018
doi: 10.1049/iet-cps.2018.5043
www.ietdl.org

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Abstract: Higher operational requirements in cyber–physical microgrid system stress the electrical system and may push it to the edge of stability. Therefore, prognosis of the imminent failures is vital. Accessing stray electromagnetic waves of power components helps in power system protection and non-intrusive prognosis of electric components faults in a cyber–physical microgrid environment. This study implements a cyber–physical approach associated between the electromagnetic waves radiated by components in the microgrid and the communication structure. To verify the same, the entire system is implemented on a real-time lab-based microgrid environment. The major problem with the stray electromagnetic waves is receiving appropriate fields. This is resolved by placing magnetic coil antennas at optimal distances and monitoring the radiated electromagnetic waves and their harmonics. Quick response code recognition technique is used to recognise the source and its corresponding healthy mode while harmonic analysis through artificial neural network helps to find the type and origin of faults. This would be an artificial intelligence-enabled system which self-optimises and acts according to the patterns. The proposed monitoring system can be utilised in any cyber–physical microgrid system especially those located in extreme/remote areas.

1 Introduction

Microgrids are a miniature version of a modern power grid that is being used and expressed as a single self-reliant entity operating as a subset of the area electric power system at distribution-level voltages with access to end-user loads, local generation sources, electricity delivery and control, and protection systems. Microgrids are smaller in size and number of assets where communication networks are a vital part of microgrid. Since communication and power systems co-exist their analysis is an indispensable part of microgrid operations. The typical aspect of microgrid is its utilisation of renewable energy resources in the prime position such as wind turbines and Photovoltaic(PV) cells [1, 2]. After a careful study of the renewable energy generation systems, it is observed that electrical part which needs monitoring is either a machine or a converter.

The eventual power grid is a multifaceted cyber–physical entity where conventional power system technologies are interleaved with new power system elements, control system components, and varied communication mediums and protocols. Interfacing these technologies might lead to an unanticipated operational behavior. Hence there is a need to detect and prevent such cyber intrusions and to provide a fall back service in the event for control residing and adversaries. Therefore, an appropriate test platform is required to evaluate the performance of these systems [3–6].

The electric components used in critical infrastructure such as power microgrids are influenced by various stresses and unexpected downtime even for a brief period due to machinery faults become challenging to counterbalance. Hence, a robust monitoring system is required to improve the life span of the components and lower the maintenance cost.

The traditional approaches used for fault detection in power components include thermal monitoring, torque monitoring, noise monitoring, and vibration monitoring. These methods have been widely used and have proven to work well under steady load conditions. However all these techniques make use of sensors that are machine specific and their corresponding monitoring is intrusive, i.e. requires to be in the system and may even require human meddling to monitor it

Recent analysis tools used in condition monitoring of components include motor current signature analysis, fast Fourier transform (FFT), wavelet analysis, and artificial intelligence (AI) [7]. Motor current signature analysis (MCSA) is a well-known technique in fault recognition. It senses an electrical signal containing current components that are direct by-product of unique rotating flux components. Any anomalies in the operation of the machine modifies the harmonic content of supply current [8]. Wavelet analysis or transform decomposes voltage and current into waves for fault diagnosis. This method is quick and effective however it is complex and requires a lot of computation. It is observed that combined MCSA and Wavelet technique yields the better results over FFT [9, 10]. The AI has a broad classification over these methods. Artificial neural networks (ANNs), fuzzy logic or neuro-fuzzy systems, and genetic algorithm are a few AI-based methods [11, 12]. They are suited for machine applications where the relation between current and speed is non-linear [13]. These AI techniques are being extended as a decision-making tool to MCSA results for condition monitoring and fault detection of machines [14–16].

In this paper, an electromagnetic sensor-based condition monitoring system in a renewable power generation facility that includes PV and wind sources is proposed. An array of magnetic coil antenna is deployed to detect radiated field from multiple optimum locations around the machine and converter simultaneously. The coils capture the fields radiated from the machine at different angles, considering the generic need of non-intrusive monitoring, and thus making the system flexible. The captured electromagnetic stray fields are then used as an input to the frequency response analysis block where the harmonic signature of these fields are analysed to detect the fault with the help of ANN. ANN based algorithms rely on impedance information for pattern recognition and their most important advantage is that it does not need to be reprogrammed, thereby being able to perform such tasks where a linear program would fail. With the combination of cyber–physical communication and trained ANN, a database would be established based on healthy conditions recorded at disparate coil locations, with different loads, switching frequency, and machine frequency to monitor the real-time system. Popular faults such as unbalanced phases and short circuits are applied to the system during training phase so that in future system would have the capability of fault prognosis. This capability is validated through experimental set up and the results are analysed.

The rest of this paper is organised as follows. In Section 2 current condition monitoring techniques of cyber–physical systems are discussed. Section 3 is the system description, detailing each unit of the arrangement. Section 4 presents hardware implementation that details the technical specification and requirements and Section 5 shows the results obtained using experimental set up. Finally, Section 6 states the conclusion of this paper.

2 Monitoring techniques for cyber–physical systems

The diagnosis methods utilised in the industry can be classified into four categories: signal-based diagnosis, model-based diagnosis, machine-theory-based analysis, and simulation-based analysis [17]. The specific methods, used in each category, are listed in Table 1.

Different fault identification techniques results are utilised in industry. The fault finding in the power components, particularly of electric machines, is relied upon to provide cautioning of imminent failures, diagnosis, and planning data for future preventive maintenance.

Fig. 1 shows the conjunction between energy system and modern network systems. Electric machines and power electronic converters and drives at various platforms such as vehicles, vessels, aircrafts, buildings, roads, or in a power system can be supposed to be mostly connected to a dedicated sensor or a sensor network. These detected signs include vibration, current, voltage, and speed. These are then sent to a nearby or remote microcontroller or computer system where the controller performs singular system control, entire system administration, or monitoring.

However there has been numerous researches regarding condition monitoring over conventional power system infrastructure, but there is no comprehensive research on smart grid platform [19–23]. There is a need of a non-intrusive technique which has a low maintenance cost and shorter downtime, that has the capability to predict the fault, locate it, and suggest a way out. A self-sustained technique can be highly desirable especially in the microgrid area which is operating in real time.

Table 1 Condition monitoring techniques used in industry [17]

Strategy category	Specific methods
signal-based fault diagnosis	mechanical vibration analysis, shock pulse monitoring, temperature measurement, acoustic noise analysis, electromagnetic field monitoring through inserted coil, instantaneous output power variation analysis, infrared analysis, gas analysis, oil analysis, RF emission monitoring, partial discharge measurement, motor current signature analysis (MCSA), statistical analysis of relevant signals
model-based fault diagnosis	neural network, fuzzy logic analysis, genetic algorithm, AI, finite element (FE) magnetic circuit equivalents, linear-circuit-theory-based mathematical models
machine-theory-based fault analysis	winding function approach (WFA), modified WFA, magnetic equivalent circuit
simulations-based fault analysis	FE analysis, time-step coupled FE state space analysis

3 Proposed system description

To achieve a proper fault prognosis in the smart grid platform, a new condition monitoring technique is proposed. The data collection is performed in a non-intrusive way by using the stray field sensors. The electromagnetic stray fields are then fed to the data acquisition system using the wireless communication and a set of algorithms are applied on collected and sampled data set to identify the fault signature. Table 2 compares the proposed and the conventional condition monitoring methods in terms of the characteristics such as being intrusive or non-intrusive, maintenance cost associated with them, corresponding downtime, fault prognosis or diagnosis, and self-sustainability. The proposed technique seems the most viable of all the methods being used or were conventionally used. Fig. 2 illustrates the typical scheme of the proposed system. Each part of the system is explained individually in the next subsections.

3.1 Stray field collection

An array of magnetic coil antennas is placed at different locations to capture the radiated magnetic field. To have the suitable position of these passive loop antenna, two parameters have been identified to be useful: angle index (α) and distance index (d). Therefore, this set of receiving coils can be utilised for any size of machine with various levels of voltage and other characteristics.

The magnetic coil is placed at the optimum location to measure the magnetic flux intensity. This flux intensity is then used for frequency analysis to comprehend the results and extract the fault harmonic information. It is also important to note that the magnetic coils used are in accordance to the MIL-STD 461 specification for low-frequency magnetic field testing. The passive loop antenna is

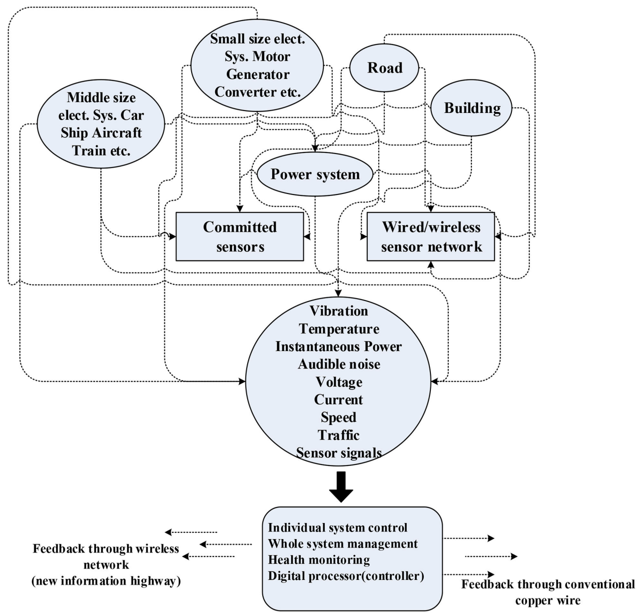

Fig. 1 *Convergence of energy system and modern network system [18]*

Table 2 Condition monitoring techniques comparison

	Intrusive/non-intrusive	Maintenance cost	Downtime	Prognosis /diagnosis	Self -sustained
Temperature Monitoring	intrusive	high	hours–days	diagnosis	no
RFEM	non-intrusive	low	minutes–days	prognosis	no
MCSA	non-intrusive	low	minutes–hours	diagnosis	yes
EFM	intrusive	high	hours–days	diagnosis	no
Proposed	non-intrusive	low	minutes–hours	prognosis	yes

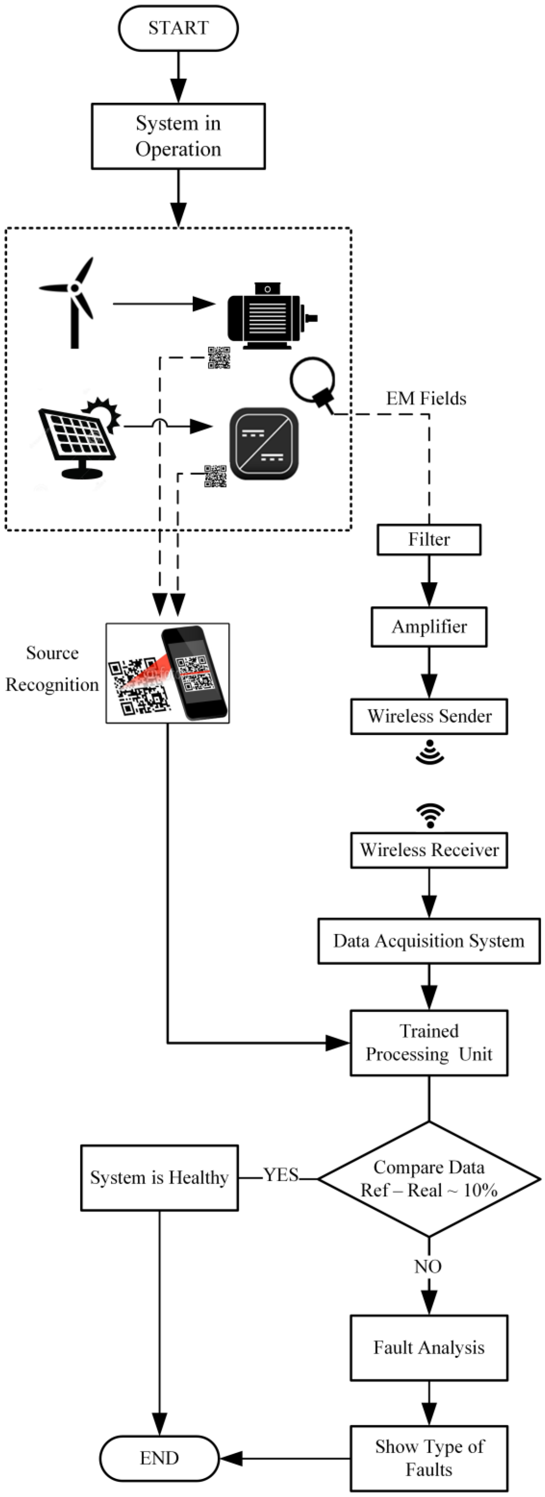

Fig. 2 *Flowchart of the proposed system*

applicable for an extensive array of magnetic field-testing applications [24–26].

3.2 Signal conditioning

The anti-aliasing filter warrants that all the captured analog signals have same phase shift, i.e. the phase angle differences and magnitudes of the signals remain unaffected [27, 28]. The stray electromagnetic waves under test are prone to high-frequency disturbances. Therefore, a low-pass filter is used to filter off the unexpected high-frequency signals. Moreover, the filter should have maximally flat (MF) characteristic, i.e. no ripples. The simplest known rational function that gives MF Low Pass Filter (LPF) characteristic is the Butterworth function which is shown in (1).

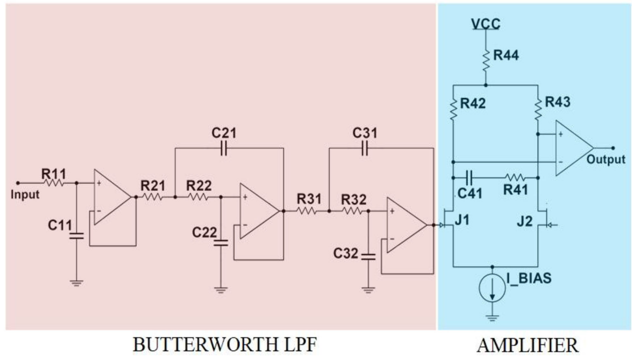

Fig. 3 *Filter and amplifier*

$$B(j\omega)^2 = \frac{1}{1 + \omega^{2n}} \qquad (1)$$

As shown in Fig. 3 after passing the obtained waves through the anti-aliasing filter, they are subjected to amplifier that amplifies the signal and cancels the noise. Noise cancellation is a type of optimal filtering that involves producing an estimate of the noise by filtering the reference input and then subtracting this noise estimate from primary input that is a composed of signal and noise. Therefore, the noise estimate should be exact replica of signal noise. The strengthened signal is then sent through the wireless unit.

3.3 Cyber–physical communication

A microgrid is a small power system with a cluster of loads and distributed generation (DG) sources operating together with DG interfacing inverters, control/support devices, and power converters within a certain area. This is where the cyber and physical worlds meet.

The integration of cyber–physical communication in microgrids introduces numerous benefits like real-time monitoring capability, fault prognosis/diagnosis, and system wide visualisation [29].

3.4 Data acquisition

The electromagnetic stray fields that are measured on the grid can be acquired using two techniques: as independent unit or within a device such as a protective relay. To perform this function, the national instrument PXI devices which are compatible with LabVIEW software, are proposed to be used [30]. To investigate the acquired data and analyse it, a trained processing unit with a set of algorithms is described next.

3.5 Trained processing unit

Trained processing unit provides a set of algorithms which when applied on data, yields the candidate frequency points and helps to analyse the frequency response under all conditions, i.e. healthy or faulty. The ANN is used to implement this function. It is necessary to select proper inputs, outputs, and structure for the network and train it with appropriate data. The important part is to adjust the weights in such a way that application of inputs yields desired results. Back propagation method is utilised for updating the weights [31].

For the reference healthy conditions, quick response (QR) code recognition is used, where for each component a unique QR code is designated. When each QR code is scanned, it gives the set of associated healthy conditions which are pre-recorded in the time domain and are changed to frequency domain using FFT. Furthermore, this response is studied for the candidate frequency points, which are deduced by repetitive tests conducted for various locations acting as an input data base for training the ANN. By using the mathematical model developed in MATLAB Simulink, ANN is trained, and the best performance is observed with 10 neurons in hidden layer. The real-time data of stray electromagnetic waves is compared with the ANN database for

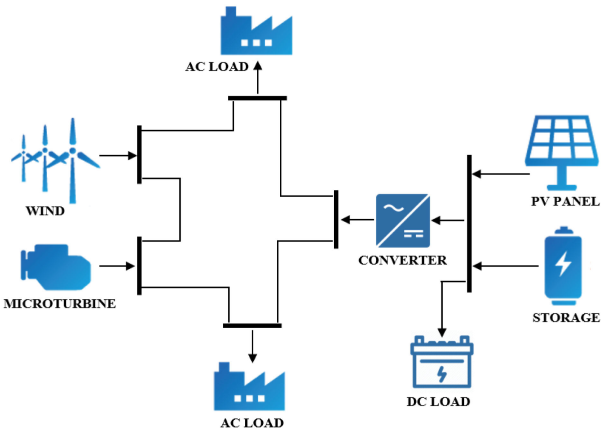

Fig. 4 *Microgrid case study configuration*

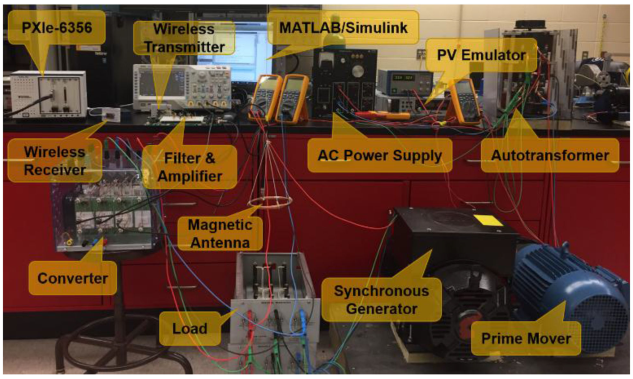

Fig. 5 *Experimental setup*

fault prognosis keeping a margin of 10% error with respect to the healthy condition.

4 Hardware implementation

4.1 Microgrid

A lab-scale stand-alone microgrid including renewable energy sources such as wind turbine, PV cells, and microturbine as energy sources along with an energy storage device (battery), transmission line emulator and both AC and DC loads is considered as the case study. Synchronous machine and DC–DC converter, which are the important components of wind energy conversion system and PV system, are selected to perform the tests. Fig. 4 shows the case study microgrid.

4.2 Test setup

The experimental setup used for validating the proposed algorithm is represented in Fig. 5. The synchronous generator used in wind energy system is MJB160XA4 208 V 11.8 kW 60 Hz three-phase generator driven by WEG 15HP 208 V 60 Hz three-phase induction motor connected to autotransformer output terminals through ESV752N06TX Lenz variable frequency drive to apply real wind speed and emulate the wind turbine. PV panels are emulated by Magna-Power XR series programmable DC power supply which is connected to a 192 W 120 V resistive load through SEMITEACH IGBT converter.

4.3 Data acquisition and communication interfaces

The stray electromagnetic waves are captured using passive loop sensor SAS-560 for a low frequency range of 20 Hz–2 MHz built in accordance to MIL-STD 461 standard for low-frequency magnetic field testing. This loop antenna has 36 turns encased in an electrostatic shielded loop. The diameter of the loop is 13.3 cm and has 10 ohms of DC resistance. Fig. 6 depicts the utilised passive loop antenna, its diameter, and the distance to ground.

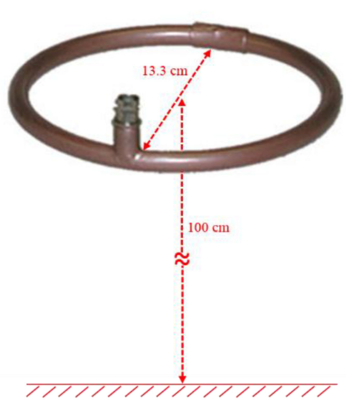

Fig. 6 *Magnetic coil antenna*

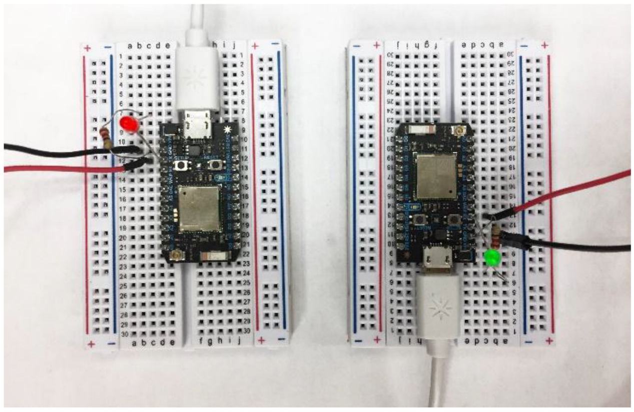

Fig. 7 *Sender and receiver Wi-Fi modules*

The measured stray fields by magnetic coil antenna go through the Butterworth filter to cancel the noises and then amplifier to strengthen the amplitude of the recorded data. The wireless communication module includes two particle photon series Wi-Fi kits with 2.4 GHz bandwidth and 65 Mbit/s data transfer rates are used as transmitter and receiver.

For cyber–physical communication, the particle photon arrangement remote modules have an effective ARM Cortex M3 microcontroller with a Broadcom Wi-Fi chip. It consists of 3.3 VDC switched mode power supply control supply, radio frequency (RF), and a user interface. Electrical variables are measured from external devices and send to the ARM CortexM3 as the data collection unit. For wireless communication, the RF section of the photon is a finely tuned impedance-controlled network of components that optimise the efficiency and sensitivity of the Wi-Fi communications [32].

The receiver end is then connected to PXIe-6356 national instrument data acquisition device with sampling rate as high as 250 Mb/cycle through SC68A connector which send the data to LabVIEW for fault diagnosis and classification. Wi-Fi communication modules are illustrated in Fig. 7.

5 Results

5.1 Test scenarios

The setup is tested by considering multiple scenarios based on combinations of four different antenna locations (A, B, C, and D), three switching frequencies of converter (2, 3, and 5 kHz), three machine frequencies (59, 60, and 61 Hz), and five faults including short-circuits and unbalanced currents. The stray magnetic fields are collected in all scenarios and frequency response, i.e. amplitude of harmonic orders up to 10 kHz are extracted by using Fourier transform. Fig. 8 shows the locations considered for magnetic coil antenna.

The frequency responses are used to train the ANN. In this case, two-layered feed forward ANN with one hidden layer and one output layer is used. LogSig and PureLin activation functions are utilised for hidden and output layers, respectively. From the total number of samples, 70% samples, i.e. 126 tests are used to train the neural network and 30%, i.e. 54 tests are used to validate the neural network. MATLAB function is used for random selection of training and testing samples. To minimise the mean squared error, gradient descend rule is applied.

5.2 Frequency analysis

The analysis of faults in power components with the help of FTT relies upon following the frequency signature of electric current waveform in each kind of fault which depends on the component's working frequency and the supply frequency. Examining the current at high rates within long periods of time is expected to accomplish an exceptional spectral resolution, which requires extensive memory space to store and process the current spectra. Since every fault produces a series of harmonics in the current and its subsequent magnetic field spectrum, some harmonic orders can be selected as candidate orders generating a unique fault signature. Fig. 9 shows the amplitude of the candidate harmonic orders as percentage of fundamental machine frequency at four selected positions to train the ANN. As shown in Fig. 9, only 17 out of the total harmonic orders are selected since they provide the highest relative error percentage compared to healthy condition at each position. To diagnose the type of fault, 5 out of these 17 harmonic orders including 11th, 51th, 101th, 135th, and 165th orders are chosen.

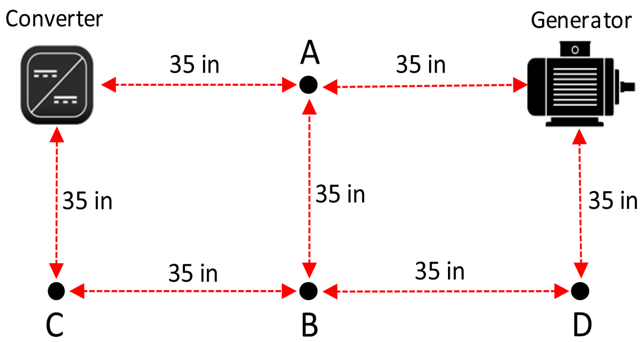

Fig. 8 *Positions of magnetic coil antenna in scenarios*

5.3 Validation

To validate the proposed fault prognosis framework, 30% of the collected data, i.e. 54 tests results are utilised. Fig. 10 represents the amplitude of the candidate harmonic orders for two sample faults including an unbalanced load current and a phase to phase short circuit fault at the synchronous machine.

The proposed algorithm successfully predicts the faulty conditions as well as type of the fault in both cases. The error between the real-time captured amplitude of the candidate harmonic orders versus pre-recorded healthy condition data are being used by ANN to prognose the fault and its type. In both cases, the frequency response for the highlighted candidate harmonic orders (11th, 51th, 101th, 135th, and 165th), which are the deciding criteria to perceive the kind of fault, indicates significant differences when compared with healthy condition. Since these harmonic orders, which are distinct in different type of faults, are utilised to diagnose unbalanced current and short circuit faults, the accuracy of microgrid fault prognosis will be acceptable.

6 Conclusion

In this paper, a non-intrusive condition monitoring framework with the capability of electric components fault prognosis in a cyber–physical microgrid is proposed. Stray electromagnetic waves of machine and converter, which are indispensable parts of any renewable energy-based microgrid setup, are measured and wirelessly transferred to data acquisition system and further algorithms are applied to recognise the faults and its type. Candidate harmonic orders of stray electromagnetic field frequency response are extracted to train the ANN. These candidate harmonic orders, which can be gathered in only a small set of values, help in substantiating the difference between the healthy and faulty conditions. This makes the system not only quick and efficient but also decreases the computational burden and memory requirements. Hardware setup is implemented to verify the

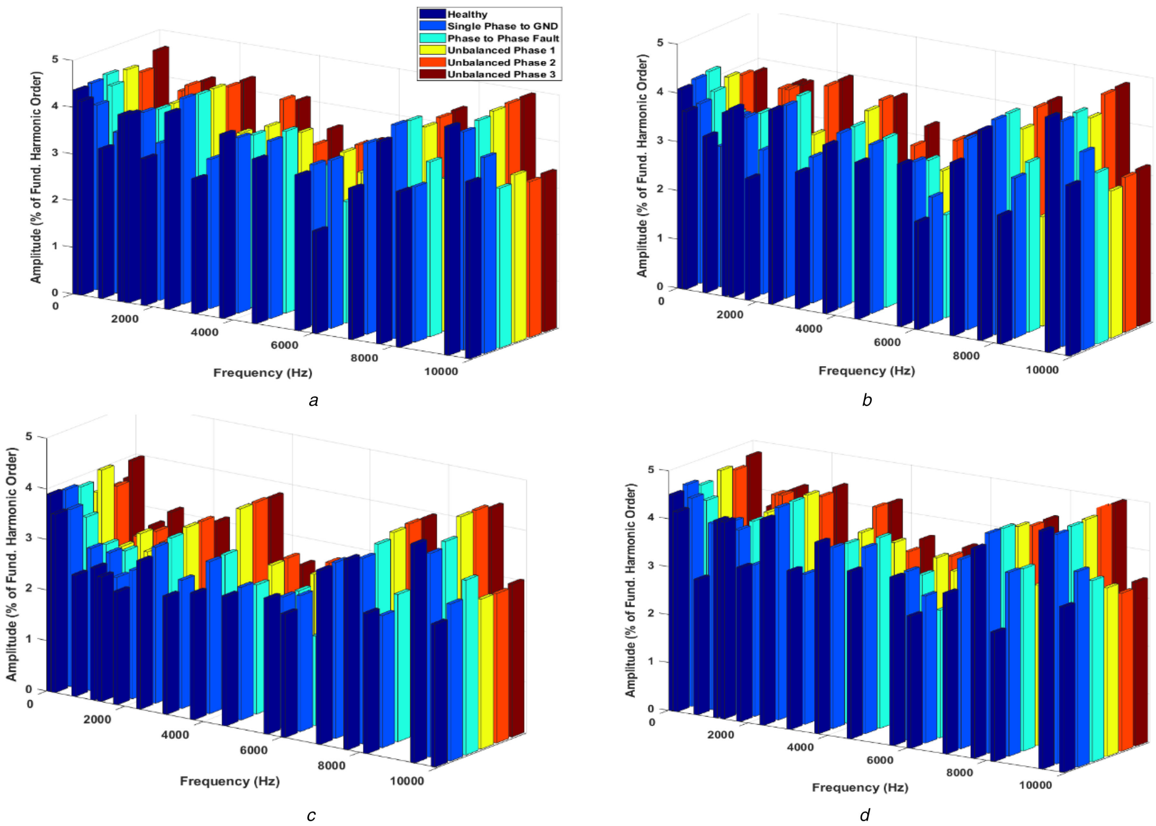

Fig. 9 *Frequency response of healthy and faulty conditions at*
(a) Position A, ***(b)*** Position B, ***(c)*** Position C, ***(d)*** Position D

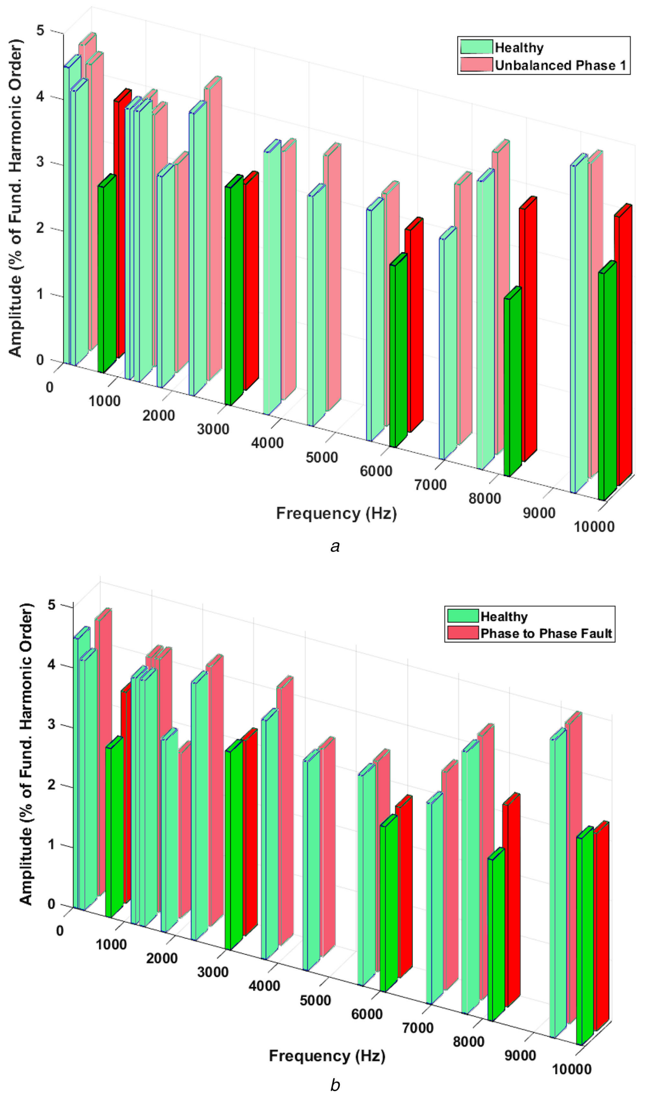

Fig. 10 *Validating the proposed fault prognosis system with random faults*
(a) Unbalanced current, ***(b)*** Phase to phase short circuit fault

functionality of the proposed algorithm in a lab-scale microgrid. Experimental results comprehend the effectiveness of the suggested system in fault prognosis.

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